APPLICATION OF THE MMAC ALGORITHM TO TREE HEIGHT AND CROWN DIAMETER ESTIMATION IN MOUNTAINOUS FOREST

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ABSTRACT:

This paper applied the multi-level morphological active contour (MMAC) algorithm to the estimation of diameter at breast height (DBH), total height, and crown width of trees in mountainous forest based on rasterized airborne lidar data. The MMAC algorithm comprises three steps: a bottom up erosion (BUE) process to identify stand candidates, a top down dilation (TDD) process to estimate the crown periphery, and an active contour model (ACM) process to delineate crown contours. The total height (LH) and crown width (LCW) can be directly calculated by the MMAC method and then used as regressors in a multiple regression model for the estimation of diameter at breast height (LDBH). The results showed that the average estimation bias of LH, LCW, and LDBH is around 0.50 m, 2.54 m, and 8.7 cm respectively.

1. INTRODUCTION

Taiwan contains a diverse variety of forest habitats, including tropical rain forest, subtropical evergreen forest, temperate forest, and alpine cold forest. These forests are distributed vertically along the central region and can be categorized into broadleaved, mixed, and conifer forests. The central mountain range peaks at 3950m and suffers occasional landslides due to above average precipitation. Manual inspection of high altitude forests is both labor-intensive and time-consuming. Airborne lidar is an active remote sensing technique in which a laser pulse is emitted towards the ground from an aircraft. Lidar makes it possible to map individual tree crowns for the purposes of forest planning and management. For the purpose of estimation of tree parameters, it is necessary to delineate the individual trees. Several methods have been developed to delineate individual trees using lidar data processing techniques including the valley-following method (Gougeon, 1995), multiple scale segmentation (Brandtberg and Walter, 1998), template matching (Pollock, 1996; Pitkänen et al., 2004), watershed segmentation (Schardt et al., 2002), local maximum filtering (Dralle and Rudemo, 1996; Popescu et al., 2003; Popescu and Wynne, 2004; Lin et al., 2006; Reitberger et al., 2007; Jang et al., 2008) and wavelet analysis (Falkowski et al., 2006). A disadvantage of these techniques is that the tree crown must be visually recognizable as a discrete object and it is necessary to have prior knowledge of crown shape or window size in order to match the crown size to the template for local maximum filtering.

In this paper, a multi-level morphological active contour (MMAC) algorithm (Lin et al, 2010) is applied to overcome these limitations. This algorithm automatically delineates tree crown area from a canopy height model (CHM) obtained from airborne lidar data. The algorithm incorporates a mathematical morphology to locate the position of each tree in the sample area and predict crown size. An active contour model method is applied to delineate a relatively precise crown shape. In this way, an estimation of total height and diameter at breast height (DBH) can be achieved.

2. STUDY SITE

The study site is located in Alishan National Forest in southern Taiwan and is centered at 23° 30' N, and 120° 48' E. Ground elevation varies between 2000 meters and 2500 meters above sea-level. The ground survey area was 0.25 hectares. The sample plot is a sugi (Chryptomeria japonica) plantation originally planted in 1914. GPS was used in conjunction with a basemap to locate the position of the sample plot. Then the boundaries of the plot were marked out with wooden stakes. Lidar data were acquired on April 20, 2007 by EFS Technologies using a BN-2 Islander plane. Flight parameters for the lidar data collection mission in the Alishan area were an operating altitude of 10,000 ft, pulse rate 40.9 KHz, scan rate 17 Hz, FOV 37 degree, and a total of 11 flight lines were taken for this area. Footprints were produced approximately 0.4 m in diameter with an average swath width of 473 m. Following boresight calibration, the lidar data sets had 0.15 cm and 2.2-20 cm of xy- and z-accuracy. Lidar data sets with canopy pulse return densities of 5.21 returns per m^2 were then used to produce rasterized surface and ground DEMs using a linear interpolation technique (0.40 m cell resolution). The Canopy

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Height Model (CHM) was calculated by subtracting the Digital Surface Model (DSM) from the Digital Elevation Model (DEM). Lidar point clouds are linked to TINs and classified based on the method proposed by Axelsson (1999; 2000). Commercial software, TerraScan, was used to implement lidar data processing. In addition 29 individual trees were chosen from the study site to carry out further analysis of tree parameters.

3. MATERIALS AND METHODS

3.1 Multi-level morphological active contour algorithm

The MMAC algorithm combines a multi-level morphological approach with the active contour model described previously.

3.1.1 MM: Mathematical morphology (MM) was proposed by Matheron (1975) and Serra (1982) as a novel geometry-based technique for image processing and analysis. Erosion and dilation are two basic operations in MM. The erosion operation can shrink or reduce the number of objects in an image. It utilizes multiple gray levels in the rasterized image moving from the bottom-up to find candidate tree blobs. The dilation operation can grow or enlarge objects in an image. It is utilizes multiple gray levels in the rasterized image moving from downward from the tree top to estimate the crown size.

3.1.2 Bottom up erosion (BUE): A step by step example of the BUE algorithm is as follows:

Suppose the image I with the minimum gray level L_1 and maximum gray level L_n.

Step 1, applying a threshold $\tau = L_1$ to the whole image I gives the first blob set S_1 which contains one connected blob which covers the whole image.

Step 2, applying a threshold $\tau = L_k$, where $k = 2,...,n$ erodes the blobs set S_{k-1} into a new blobs set S_k. Many blobs are eroded to smaller blobs or separated into several smaller blobs.

Step 3, the blobs which contain a limited area α with a rounded shape are considered as possible stand candidates and the erosion process ends. To measure the roundness of a blob shape the following equations are used: Eq. 1 and Eq. 2. Eq. 1 and 2 are applied by calculating the minimum radius $\gamma_{\min}$ and the maximum radius $\gamma_{\max}$ from the center c_{blob} of the blob shape. The difference d_r between $\gamma_{\max}$ and $\gamma_{\min}$ is used to measure the circularity of the blob. When the difference d_r shows a low variance, this indicates that the blob has a high degree of circularity. When d_r is zero, the shape is a perfect circle. It is assumed that the circularity of a blob is potentially a good indicator for a tree candidate within a forested area.

$$\begin{cases} \gamma_{\min} = Min(dist(b(i,j), c_{blob})) \\ \gamma_{\max} = Max(dist(b(i,j), c_{blob})) \\ d_\gamma = \gamma_{\max} - \gamma_{\min} \end{cases} \quad (1),$$

where $b(i,j)$ is the boundary pixel of the blob, is the center of the shape of the blob and is the difference between $\gamma_{\max}$ and $\gamma_{\min}$

$$dist(x,y) = \sqrt{(x-y)^2} \quad (2),$$

where $dist(x,y)$ is the distance between x and y.

3.1.3 Top down dilation (TDD): After forest stand candidates have been identified by BUE, each candidate becomes a seed for a tree crown (called a seed blob). A TDD image processing technique is applied to each of the seed blobs to estimate the tree crown area around each of the candidates. Starting at the top level and moving gradually down through the image data to the bottom level, the seed blob is expanded. During the dilation process, the pixels surrounding the seed blob are grown outwards. The dilation process stops if one of the following conditions is satisfied. The first condition occurs when the circularity of the dilated shape d_γ (as calculated in Eq. 1) exceeds a certain threshold value. The second condition occurs when the value of adjacent pixels show a sudden variation in height. This sudden change is generally due to one of two reasons. Either the outside periphery of a tree crown has been located or the point where two connected crowns with a significant height difference has been located. In the first case pixel values will drop off suddenly, while in the second case pixel values may rise suddenly. By enforcing these restrictions the dilation process is guided towards producing a circular shape similar to the natural shape of a tree when viewed from above.

3.1.4 Active contour model (ACM) algorithm: In a densely packed forest, TDD produces an area smaller than the actual tree crown. The reason is that when trees are competing for the same space, tree crowns often overlap or merge together. ACM can extend the boundary to find the real crown radius with a round boundary similar to that of a visible tree crown. The ACM was developed by Kass et al. (1988). The contours of the tree crown obtained using the TDD technique are used as initial control points for the ACM process. ACM defines internal energy and external energy. Internal energy is generated from the attraction between control points. It makes the contours more rounded and removes sharp edges. External energy is generated from the attraction of high gradient crown edges. Through the repeated interaction of these two energies, the crown contours become rounded and eventually fit the crown edges.

3.1.5 MMAC: The MMAC algorithm is comprised of three steps. The first step uses bottom up erosion (BUE) to process CHM data and locate the stand candidates within a forested area. The second step uses a top down dilation (TDD) technique to estimate tree crown periphery points by growing outwards from stand candidate center points. The third step uses ACM to modify the periphery points and delineate the contours of the tree crown boundary.

3.2 Crown diameter and total height measurements

The studies made by Popescu et al. (2003) and Popescu (2007), show that tree height and crown diameter (crown width) have a linear relationship with DBH. Popescu (2007) showed through linear regression that an RMSE (estimation bias) of 4.9cm is approximately 18% of the average DBH for all measured trees, with an R^2 value of 0.87. In this study, 30 trees were selected in a mountainous forest. Crown width (CW) was obtained by averaging the horizontal diameter (East-West length) and vertical diameter (North-South length). Total heights (H) of trees were measured using a laser ranging device, MDL. After MMAC processing, the lidar-derived tree height (LH) was estimated using the crown tip height. Lidar-derived tree crown width (LCW) was calculated by doubling the average distance from the center of the tree crown to the 4-directional (East, South, West, and North) crown boundary. MMAC estimates of

TH, CW, and DBH from lidar data were then evaluated against ground survey data.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Tree height estimate evaluation

Figure 1 shows the CHM data of the 30 trees in the sample. In this figure, the irregular polygon shows the crown boundary delineated by the MMAC method. The lidar-detected height (LH) of a tree was determined by the largest pixel value within the MMAC delineated crown boundary. Figure 2 demonstrates the closeness of fit between the lidar detected height (LH) and ground measured total height (H) of the sample trees. It can be observed that the bias of height estimates ranges from -0.88m to 0.99m, and the average and standard deviation of the absolute bias are 0.49m and 0.29m. Obviously, the lidar derived LH height is representative of the ground measured total height H in this sample.

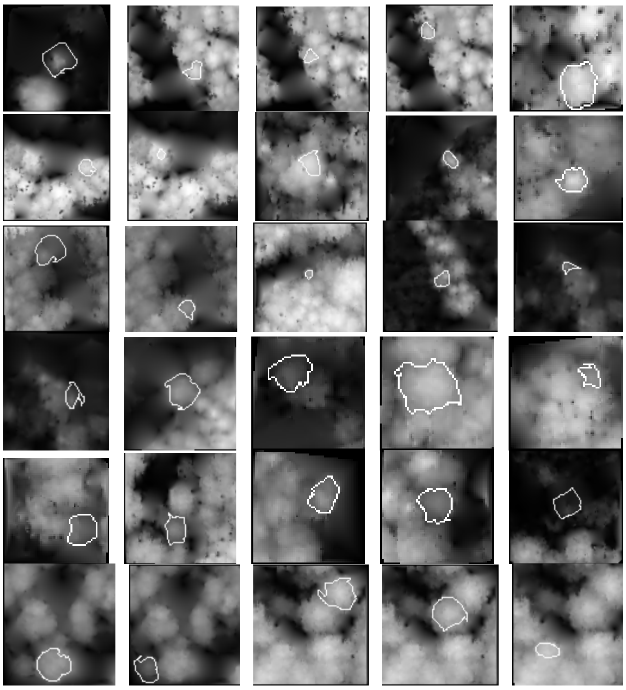

Figure 1. Sample 30 trees with MMAC delineated crown boundary.

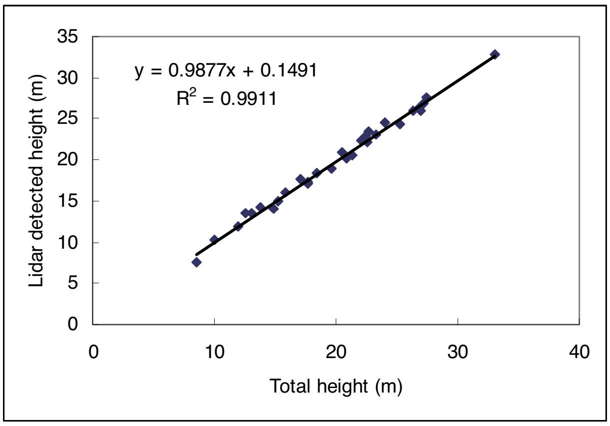

Figure 2. Relationship between the lidar detected height (LH) and observed total height (H) of the sample trees. A linear regression model with a R^2 value of 0.99 indicating a good fit between LH and H.

4.2 Crown width estimate evaluation

Figure 3 shows the scatter plot of lidar delineated crown width (LCW) vs. ground measured crown width (CW). In this figure, a linear model is fitted with a R^2 value of 0.17 which indicates a poor estimation of lidar data. In this study, the LCW had a bias ranging from -4.2m to 5.3m. The average and standard deviation of LCW estimation bias was 2.54m and 1.60m respectively.

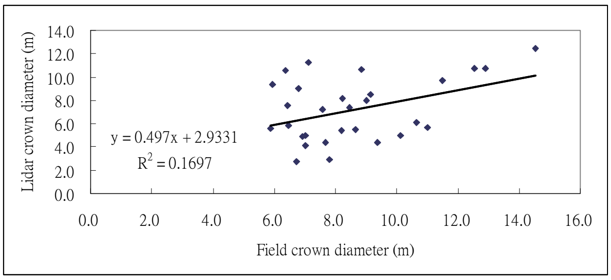

Figure 3. A scatter plot of LCW vs. CW of the tree samples.

4.3 DBH estimation model and its deviation

We used ground measured crown width and total height as predictors to estimate the diameter at breast height of trees. Equation (3) shows the multiple regression model of DBH estimates based on the ground measurements of tree crown and total height. The fitness of this model (R^2=0.80) can be examined from the figure 4.

$$DBH = 4.08 \cdot CW + 2.11 \cdot H - 17.85 \tag{3}$$

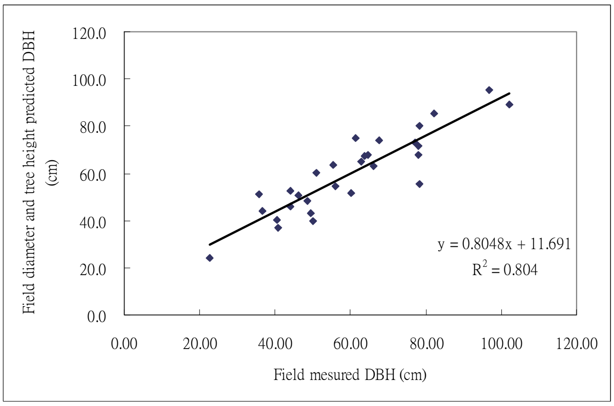

Figure 4. Relationship of the field-measured DBH vs. the predicted DBH.

$$LDBH_1 = 1.91 \cdot LCW + 2.52 \cdot LH - 4.19 \tag{4}$$

$$LDBH_2 = 0.16 \cdot LCA + 2.50 \cdot LH + 1.93 \tag{5}$$

We used lidar CHM crown width (LCW), crown area (LCA), and tree height (LH) as regressors in a multiple linear regression analysis. Estimates of DBH (LDBH) can be calculated by Eq. (4) or Eq. (5). Figure 5 shows the scatter plot of DBH vs. $LDBH_1$ from which a linear pattern is obtained. About 68% of the variation in DBH could be determined by LCW and LH (R^2=0.68). The predictive capability of LCW and LH is very close to LCA and LH because the R^2 of the $LDBH_2$ model (Figure 6) is almost equal to $LDBH_1$ model.

Ground measured DBH of a tree estimated by ground measured crown width and total height has a bias of 6.3cm. The estimation bias is evaluated as approximately 11% of the average value of all DBH measurements. When we use the crown width estimates and the total height estimates from lidar data as predictors, the diameter estimates LDBH has a bias of 8.7cm, which is approximately 15% of the average value of all DBH measurements.

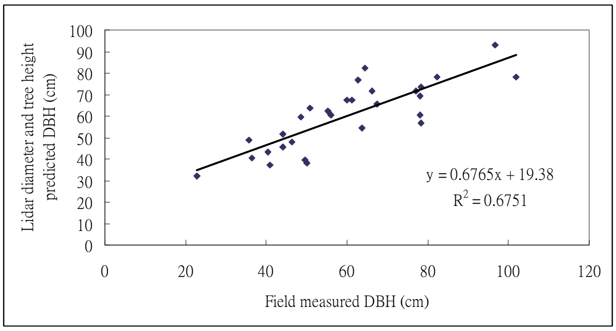

Figure 5. Relationship of field-measured DBH vs. lidar predicted diameter estimates ($LDBH_1$) using LCW and LH as predictors.

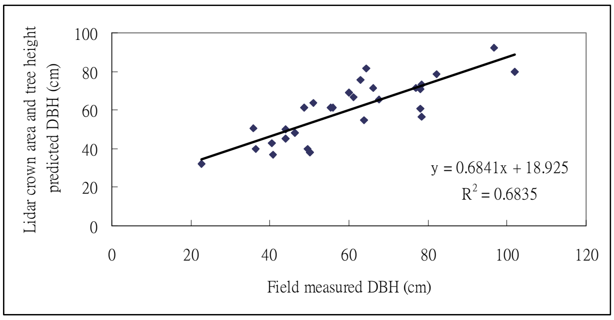

Figure 6. Relationship of field-measured DBH vs. lidar predicted diameter estimates ($LDBH_2$) using LCA and LH as predictors.

5. CONCLUSIONS

This paper applied an automatic method of crown mapping, the Multi-level Morphological Active Contour (MMAC) algorithm, to identify and delineate tree crowns in mountainous forest. A sample of 30 trees (sugi and red cypress) in a conifer forest on Alishan Mountain was selected. The MMAC method was evaluated for its ability to detect parameters of trees, such as tree height, crown width, and diameter at breast height. Comparing the parameters derived from rasterized airborne lidar data to ground survey data, we found that tree height estimates were much more acceptable than the crown width estimates. Using the multiple linear regression technique, we found that estimates of both tree parameters were able to predict the diameter of trees at breast height. Briefly stated, the coefficient of determination (R^2) for the DBH regression model using lidar-based parameters was 0.68 which is 0.12 less than the R^2 of the DBH estimation model using ground surveyed parameters.

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